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# Short Term National Airspace System Delay Prediction Using Weather Impacted Traffic Index

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**This paper describes a method to predict delay in the National Airspace System for durations of up to two hours. Various linear autoregressive model structures with exogenous inputs were implemented to perform the delay prediction. Current and forecast weather impacted traffic indices and air traffic volume were used as inputs to the system while the air traffic delay is the predicted output of the model. The refined methodology for generating the weather impacted traffic indices, together with the high-update-rate of Corridor Integrated Weather System is well suited for real-time delay prediction. An adaptive scheme was implemented to provide both weather-related and non-weather-related delay predictions depending on the weather and air traffic condition. The method will benefit air traffic management by facilitating the development of strategies to reduce delays, cancellations, and other costs during the day of operations in various weather conditions.**

## I. Introduction

National Airspace System (NAS) has been studied both for identifying the air traffic delay models and for improving the air traffic flow management efficiencies. Studies show that 70% of all delays in the NAS are related to weather and, of these 60% are caused by convective weather[1]. For good weather days, factors other than weather including air traffic demand-capacity imbalances, equipment outages and runway conditions also have to be characterized. To guide flow control decisions and develop strategies to reduce delays, cancellations, and other costs during the day of operations in various weather conditions, it is useful to create a real-time delay prediction model and provide the delay prediction for several hours.

Efforts have been made in the past few years to identify the correlation between weather and delay on a daily basis both at the regional and the national level. The most promising concept is to use the Weather Impacted Traffic Index (WITI), which was first introduced by Callaham et al[2]. Sridhar[3,4] and Chatterji[5] expanded the concept and built various daily NAS delay estimation models by linear regression. Furthermore, the NAS WITI has been combined with regional WITI and other nonlinear components. Klein[6] developed objective measures of the combined impact of traffic demand and weather on the air traffic system by further combining en route WITI, terminal WITI and queuing delay to develop a new metric, the NAS Weather Index (NWX). Hansen[7] developed models involving relationship between observed airline delay and several causal factors, including traffic, airport weather, en route convective weather, and weather forecast accuracy. All of these models are static and provide a good correlation between weather and average air traffic delay on a daily basis. A dynamic model, which expands the level of detail to smaller time intervals, is lacking in the past research. Another variant of WITI can be developed using weather forecast products, which may increase the accuracy of the delay prediction. Klein[8] studied a forecast WITI, named WITI-forecast accuracy (WITI-FA), based on the Collaborative Convective Forecast Product (CCFP). Since the CCFP is updated every 2 hours, it is not well suited for real-time air traffic delay prediction, which requires high update rates.

The FAA Aviation System Performance Metrics (ASPM) reports actual delays at a sampling time interval of quarter hour and up. The objective of this paper is to predict delays for the next two hours using current and past information. The short-term delay prediction system uses WITI, predicted WITI, and air traffic demand as inputs and provides estimates of NAS delay as outputs. The methodology used for WITI computation[3-5] is refined to generate both WITI and predicted WITI based on the Corridor Integrated Weather System (CIWS)[9] using the Future ATM Concepts Evaluation Tool (FACET)[10,11]. The predicted CIWS-WITI, which is updated every 5 minutes with 5-minute forecast time-steps, is more suitable for short-term delay prediction compared to the WITI based on CCFP,

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which is updated every 2 hours with 2-hour forecast time-steps. Delay estimation models are limited to using convective weather information only due to the unavailability of suitable models for other weather conditions like ceiling-and-visibility, high surface winds and icing. As non-convective weather models improve, they can be incorporated as additional variables in the estimation methods[12]. For good weather days, the delays are less related to the weather but more related to other factors including equipment outages, runway conditions, and air traffic demand-capacity imbalances. An adaptive scheme to switch between models based on weather conditions is implemented to provide both weather-related and non-weather-related delay predictions.

The remainder of the paper is organized as follows. Section II provides the definition of WITI, delay, and quantity of air traffic demand, which form the components of the NAS delay models. Next, the prediction models are described in Section III. Three different models and the methods to compute the model parameters are formulated. The results and performance of the prediction models are demonstrated in Section IV. The adaptive scheme to obtain the optimal solutions is also introduced in this section. Three months of data during the summer of 2007 are used to validate the models. Finally, summary and conclusions are described in Section V.

## II. Factors Affecting Delay

This section describes and analyzes the traffic data, weather data and delay observations available in the various databases that can be used to develop empirical models relating these variables.

### A. Computation of WITI

WITI is an indicator of the number of aircraft affected by weather. The computation of WITI consists of: 1) assigning a value of one to every grid cell $W_{i,j}$ of the weather grid $W$ where severe weather is indicated and zero elsewhere, 2) counting the number of aircraft in every grid cell $T_{i,j}$, and 3) computing the WITI at an instant of time $k$ (typically at one-minute intervals) as follows,

$$WITI(k) = \sum_{j=1}^{m} \sum_{i=1}^{n} T_{i,j}(k) W_{i,j}(k), \tag{1}$$

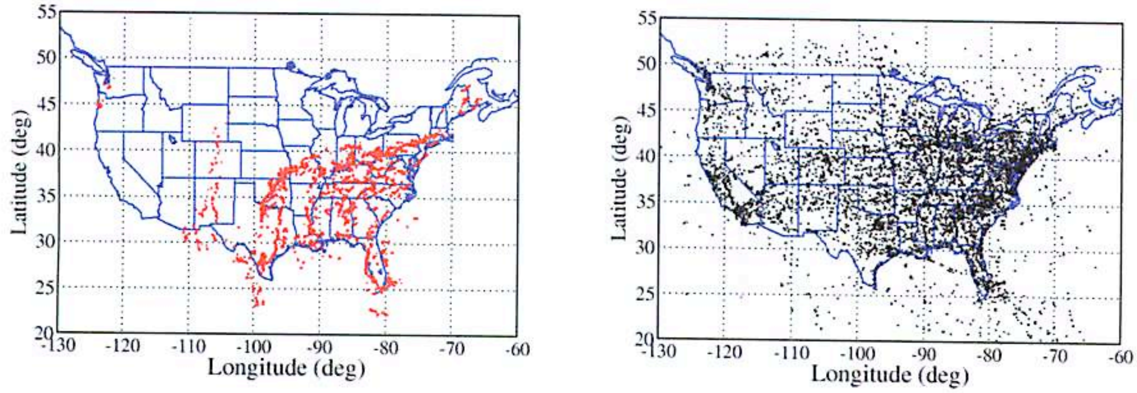
where $n$ is the number of rows and $m$ is the number of columns in the weather grid.

Currently, most WITI computations are done using the NOWRAD weather data[3-5]. NOWRAD weather data consists of 16 radar data levels (called color levels) reported in the weather grid. The original source of NOWRAD data is the Next Generation Weather Radar system (NEXRAD), which comprises approximately 160 Weather Surveillance Radar sites throughout the United States and selected overseas locations. The National Climatic Data Center (NCDC) archives and disseminates these processed data in binary files. Binary data in the files are then converted into text data and the resulting 16 levels are reduced into 7 Video Integrated Product (VIP) levels. The resulting VIP levels, 1 through 6, indicate light precipitation, light to moderate rain, moderate to heavy rain, heavy rain, very heavy rain with the possibility of hail, and very heavy rain and hail with the possibility of large hail. Level zero indicates absence of rain. Severe weather is indicated by VIP level three or higher.

Since NOWRAD data are provided in a grid, the traffic counts derived from the aircraft position data have to be mapped to the same grid. This mapping is straightforward because aircraft position data are provided in terms of latitudes, longitudes and altitudes. More details about traffic count generation can be found in[5].

Figure 1a shows the locations where severe weather is indicated at 3 PM Eastern Standard Time (EST), on 28 June 2007. The weather grid consists of 1837 rows and 3661 columns, which are approximately one nautical mile wide. Figure 1b shows the corresponding locations of aircraft in the weather grid based on historical demand. Finally, element-by-element multiplication of the two grids in Fig. 1 and summation in step 3 (see equation (1)) results in WITI at 3 PM on 28 June 2007. Observe from equation (1) that the unit of WITI is number of aircraft since $W_{i,j}$ takes on values of one or zero. Thus, WITI is a weather weighted traffic count.

The computation of WITI and its use in delay prediction in this paper are based on the weather information provided by the Corridor Integrated Weather System (CIWS). CIWS, created by MIT Lincoln Laboratory, provides 2-hour convective forecasts, every 5 minutes during the first hour and every 15 minutes during the second hour, updated every 5 minutes. Different contour levels indicate the level of weather severity. Although the CIWS does not cover the entire NAS, the coverage includes a major portion of the high traffic density eastern United States. The definition of WITI used in equation 1 has to be modified to accommodate the CIWS weather formats.




(a) Weather (b) Expected traffic

**Figure 1: Regions of severe weather and expected traffic at 3PM EST on June 28, 2007.**

The computation of WITI is modified in the following way: 1) find all the weather contours of interest $W_i$, (2) find whether aircraft $T_j$ in the reference air traffic is inside contour $W_i$, and 3) computing the WITI at an instant of time $k$ (typically at one-minute intervals) as follows,

$$WITI(k) = \sum_{j=1}^{m} \sum_{i=1}^{n} \begin{cases} 1, \text{if } T_j(k) \text{ is inside } W_i(k) \\ 0, \text{if } T_j(k) \text{ is outside } W_i(k) \end{cases}, \tag{2}$$

where $n$ is the number of weather contours and $m$ is the total number of aircraft. The CIWS-WITI generation method has been integrated into the Future ATM Concepts Evaluation Tool (FACET)[10-11].

Figure 2a shows a FACET display with the CIWS weather and the corresponding reference traffic. The WITI computation is to find the number of aircraft within the weather contours of a certain level, as formulated in equation (2). As an example, Fig. 2b shows two arbitrary level 3 contours and a total of five aircraft, which are represented by triangles, within the contours. Therefore, the WITI count for this situation is 5. A 24 hours period starting at 04:00 AM (EST), since most of the aircraft departing on the previous day would have landed and new aircraft are just starting to depart, is used to define a day. The WITI is generated at the sampling rate of 1 minute,


(a) Entire NAS (b) Zoom-in

**Figure 2. FACET display showing CIWS weather and air traffic.**

consistent with the traffic update data feed. The CIWS data is updated every 5 minutes and is considered static during the 5-minutes interval. In Fig. 3, the blue line shows the CIWS-WITI as a time series on June 28, 2007. The hourly WITI is defined as the average WITI within the hour, as shown by red dots in the figure.

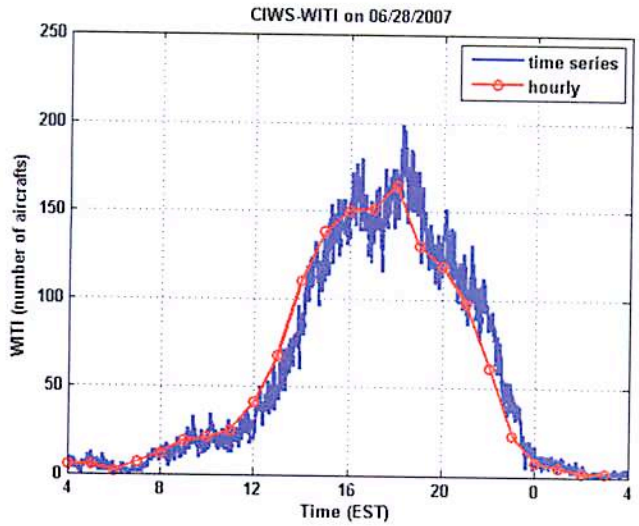
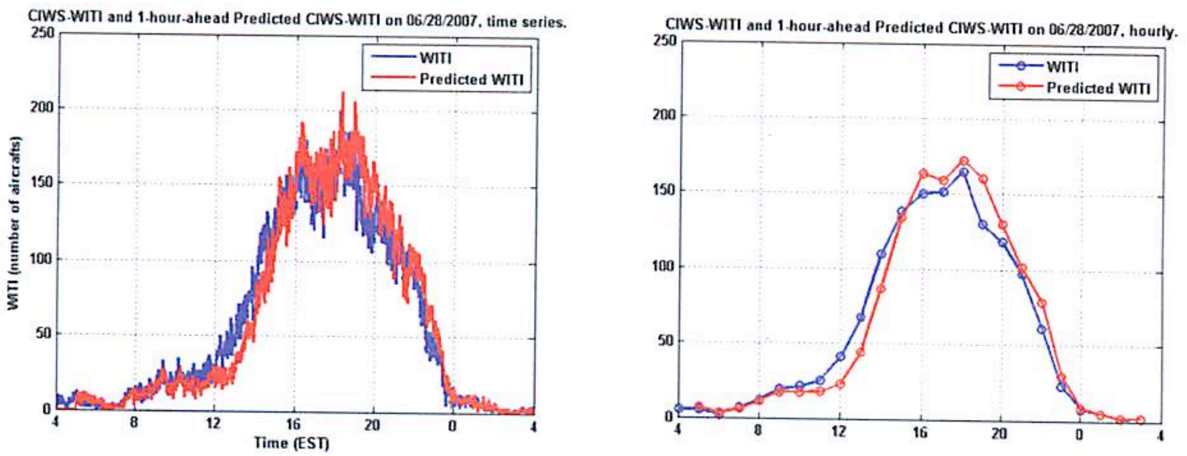



**Figure 3. CIWS-WITI as a function of time on June 28, 2007.**

In addition to the actual weather data, CIWS provides the weather forecast up to two hours ahead. The Predicted-WITI is computed similar to the WITI. Instead of using the current weather information, the weather forecast along with the reference traffic is used to generate the Predicted-WITI. In equation (2), $W_i$ represents the weather forecast contours and $n$ is the number of forecast weather contours. Figure 4a shows the comparison between CIWS-WITI and the 1-hour predicted CIWS-WITI on June 28, 2007. The time series of the two look similar. The hourly WITI and predicted WITI are shown in Fig. 4b. In this case, at given hour $h$, the predicted WITI provides an additional WITI forecast at the next hour, $h+1$. Even if there is some discrepancy due to the inaccuracy of the weather forecast, the additional information still may benefit the delay prediction, as discussed in the next section.



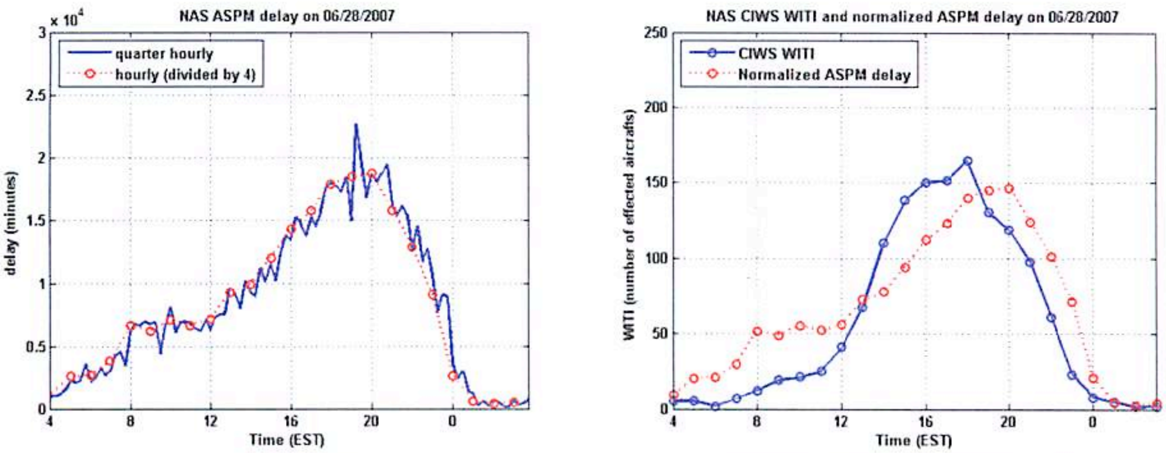

(a) Time series (b) Hourly

**Figure 4. CIWS-WITI and 1-hour-ahead predicted WITI on June 28, 2007.**

### B. Delay

The delay observations provided by the FAA Aviation System Performance Metrics (ASPM) are used in this paper. ASPM provides performance data for 75 domestic airports at two different sampling rates, hourly and quarter hourly. Figure 5 shows the NAS ASPM schedule arrival delay on June 28, 2007. As can be seen from Fig. 5a, the quarter hourly delay data is noisy with many high frequency components, and is unsuitable for delay prediction. Instead, sampling at 1 hour per period, shown as red dots in the Fig. 5a, provide a smoother curve and is used for developing the prediction model in the next section.

Next, the correlation between the ASPM scheduled arrival delay and CIWS-WITI is examined. Assume the hourly ASPM delay is $\{d(h)|h=1...24\}$ and the CIWS WITI is $\{w(h)|h=1...24\}$ on June 28, 2007, as shown in Fig 5b. There is similarity between the shapes of the two curves in the figure. As a reference, the correlation coefficient between $d(h)$ and $w(h)$ is .93. This result suggests that the hourly WITI is highly correlated with the hourly ASPM delay and could be used to build a linear model for the delay prediction.




(a) ASPM delay (b) CIWS-WITI and ASPM delay

**Figure 5. The NAS ASPM delay on June 28, 2007.**

## III. Prediction Model

Research done by Sridhar[3,4] and Chatterji [5] shows a strong linear correlation between air traffic delay and daily WITI. Unlike previous research, which is focused on the effect of weather on total delay during a day, this research correlates weather and delay on an hourly basis and uses the estimation model to predict delay for the next two hours. The availability of certain types of weather data and actual past delay every 15 minutes is used in the development of the correlation. Several different estimation models are considered depending on the availability of past weather, forecast of future weather, past delay, past and future air traffic demand. The weather and traffic data is translated into WITI and WITI forecast. Averaging procedures discussed in the previous section is used to smoothen the noise in the 15 minutes updates. Various linear autoregressive model structures with exogenous inputs (ARX) are used to perform the delay prediction[13-15]. At a given time $t$, all the available observations, which include the current and past WITI and delay, and the reference air traffic volume is used for delay prediction. Furthermore, the predicted CIWS-WITI up to 2 hours ahead is used in the filtering ARX model to provide additional information. The rest of the section describes three specific estimation and prediction models.

### A. Predicting ARX Model with WITI

For real-time delay, or live prediction, the future delay is predicted based on the current and past information about the delay. Assume $d(t)$ is the delay, and $w(t)$ is the WITI, at a given time $t$, the available observation set consists of $\{d(i)|i=1...t\}$ and $\{w(i)|i=1...t\}$. The $n^{th}$ order, $p$-steps-ahead predicting ARX model can be formulated as,

$$\hat{d}(t+p) = \sum_{k=0}^{n-1} \begin{bmatrix} a_k & b_k \end{bmatrix} \begin{bmatrix} d(t-k) \\ w(t-k) \end{bmatrix} + d_0 + e(t), \tag{3}$$

where $\hat{d}(t+p)$ is the delay prediction at time $t+p$, $d_0$ represents a delay offset which is not weather-related, and $e(t)$) is the prediction error. The model coefficients $a_k$, $b_k$ can be found by solving the least-square solution to the equation

$$\begin{bmatrix} d(t) \\ \vdots \\ d(n+1) \end{bmatrix} = \begin{bmatrix} d(t-p) & \cdots & d(t-p-n+1) & w(t-p) & \cdots & w(t-p-n+1) & 1 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ d(n) & \cdots & d(1) & w(n) & \cdots & w(1) & 1 \end{bmatrix} \begin{bmatrix} a_0 \\ \vdots \\ a_{n-1} \\ b_0 \\ \vdots \\ b_{n-1} \\ d_0 \end{bmatrix} . \tag{4}$$

**B. Filtering ARX Model with WITI and Predicted WITI**

The predicted WITI can be used in the prediction model. At a given time $t$, in addition to $d(k)$ and $w(k)$ up to time $t$, the predicted WITI $\{w_p(k)|k=1...t+p\}$ is also available. The $n^{th}$ order, $p$-steps-ahead filtering ARX model is described by the equation

$$\hat{d}(t+p) = \sum_{k=0}^{n-1} \begin{bmatrix} a_k & b_k \end{bmatrix} \begin{bmatrix} d(t-k) \\ w_p(t-k+p) \end{bmatrix} + d_0 + e(t) . \tag{5}$$

where $\hat{d}(t+p)$ is the delay prediction at time $t+p$, $d_0$ represents a delay offset which is not weather-related, and $e(t)$ is the prediction error. Note that $w_p(t+k)=w(t+k)$, when $k<=0$. The model coefficients $a_k$, $b_k$ can be found by solving the least-square equation

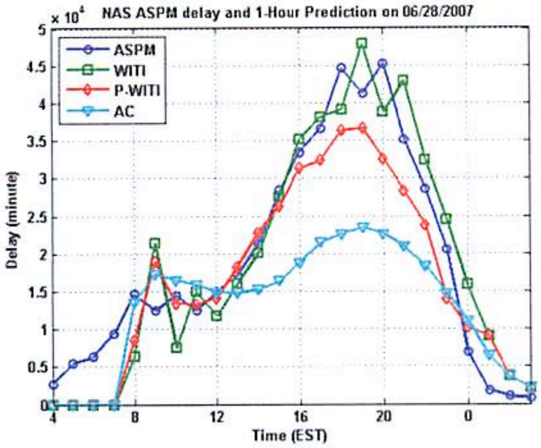
$$\begin{bmatrix} d(t) \\ \vdots \\ d(n+p) \end{bmatrix} = \begin{bmatrix} d(t-p) & \cdots & d(t-p-n+1) & w(t) & \cdots & w(t-n) & 1 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ d(n) & \cdots & d(1) & w(n+p) & \cdots & w(p) & 1 \end{bmatrix} \begin{bmatrix} a_0 \\ \vdots \\ a_{n-1} \\ b_0 \\ \vdots \\ b_{n-1} \\ d_0 \end{bmatrix} . \tag{6}$$

**C. Filtering ARX Model with air traffic volume**

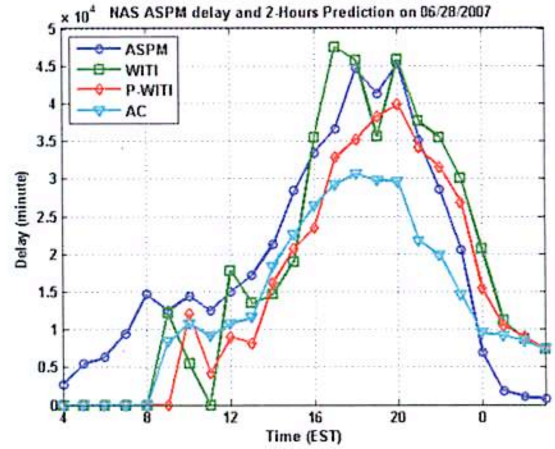
Not all the air traffic delays are weather related. WITI provides weather related information and is best to predict the weather related delay. The prediction model without the weather information is built to predict delay that is not correlated with the weather. Examining the air traffic delay during a day, it is evident that high delay usually appears during peak traffic times. In the other words, air traffic volume is highly correlated with delay. The air traffic volume on the reference day is used for this model. The total number of aircraft at time $t$, $a_c(t)$, in the region covered by CIWS will be used to develop air traffic volume prediction model. Note that $a_c(t)$ is a known quantity throughout the day. At a given time $t$, the observations of $\{d(i)|i=1...t\}$ and $\{a_c(i)|i=1...t+p\}$ are available. The $n^{th}$ order, $p$-steps-ahead filtering ARX model is formulated the same way as in equation (5), replacing $w_p(t)$ with $a_c(t)$. The model coefficients $a_k$, $b_k$ can be found by solving the least-square equation (6), replacing $w(t)$ with $a_c(t)$. This model will be compared with models using weather information.

## IV. Results

Three prediction models, predicting ARX model with WITI (WITI Model), filtering ARX model with predicted WITI (P-WITI model), and filtering ARX model with air traffic volume (AC model), are described in the previous section. Next, these models are used with the data for June 28, 2007 at the sampling rate of 1 hour. The delay prediction starts at the fifth data point, or 8 AM(EST) because at least four data points are needed to estimate the model coefficients. At a given hour $h$, the observations of $\{w(i)|i=1...h\}$, $\{w_p(i))|i=1...h+2\}$, $\{a_c(i)|i=1...24\}$ and $\{d(i)|i=1...h\}$ are available. For the one-hour delay prediction, the first order models are used and the results are shown in Fig. 6a. For the two-hour delay prediction, the second order models are used and the results are shown in Fig 6b.




(a) 1-hour prediction




(b) 2-hour prediction

**Figure 6. The NAS ASPM delay and prediction on June 28, 2007.**

The data for the months June, July and August 2007 are used to compare the performance of delay prediction with the three models. Results show that for the 1-hour prediction, the first order WITI model performs well, and for the 2-hour prediction, the second order P-WITI model works well. It is reasonable to assume the predicted WITI provides more information with farther prediction. AC model performs better than the others during most of the low delay days. Further, it was found that the WITI counts are low in these cases. When the WITI is low, the delay is more likely to be related to the air traffic volume than weather.

Using these trends, an adaptive scheme is developed that switches between WITI/P-WITI model and AC model based on the WITI/P-WITI value. At a given hour, t, WITI values $w(t)$, $w(t+1)$, .., and $w(t+p)$ are examined. If the WITI and predicted WITI values are below a certain number, δ, then AC model is used for predicting the delay for the next hour. Otherwise, either WITI or the P-WITI model is used for predicting the delay for the next hour. A value of δ=200, which is based on historical WITI variations for this region, is used in the adaptive scheme. The prediction error of the new WITI and AC hybrid model (WITI-AC model) and P-WITI and AC hybrid model (P-WITI-AC) are significantly lower than the other models. The relative prediction error is defined as,

$$e_{RMS} = \sqrt{\frac{\sum_{i=5}^{24}(d(i)-\hat{d}(i))^2}{20}}, \tag{7}$$

where $d(i)$ is the actual delay, and $\hat{d}(i)$ is the predicted delay. Note that the prediction starts at the fifth data point, which is at 8 AM (EST). The root-mean squared errors, in minutes, for the prediction models for June 28, 2007 are (a) for one-hour prediction, WITI=5336, P-WITI=5254, AC=10879, Adaptive=4557, and (b) for two-hour prediction, WITI=9295, P-WITI=8583, AC=12388, and Adaptive=8384.

Figure 7 shows the results of one-hour prediction using three different models, namely, the ARX model using WITI (WITI), the ARX model using air traffic volume (AC), and the adaptive model (Adaptive) for summer 2007. In most cases, the WITI model performs better than the AC model, and the Adaptive model has the least error. The cases where the Adaptive model does not produce the least error, the magnitude of the errors produced by all the three models is small and close to each other (within 10%). To provide a sense of scale, for each day during the three-month period, Figure 8 shows the total ASPM delay in the Centers covered by the CIWS weather data. The total daily delay during this period varies from a low of 70,000 minutes to a high of 580,000 minutes. Figure 9 shows the results for two-hour delay prediction using the three models, namely, the ARX model using predicted WITI (P-WITI), the ARX model using air traffic volume (AC), and the adaptive model (Adaptive). The performance of the models for the two-hour delay prediction is similar to the one-hour prediction. In both cases, the adaptive models provide better prediction than the others. However, as expected, the magnitude of the errors for the two-hour prediction is higher than that for the one-hour prediction. The average error, in minutes, for the prediction models for summer 2007 are (a) for one-hour prediction, WITI=4024, AC=6119, Adaptive=3743, and (b) for two-hour prediction, P-WITI=6205, AC=7096, and Adaptive=5851.

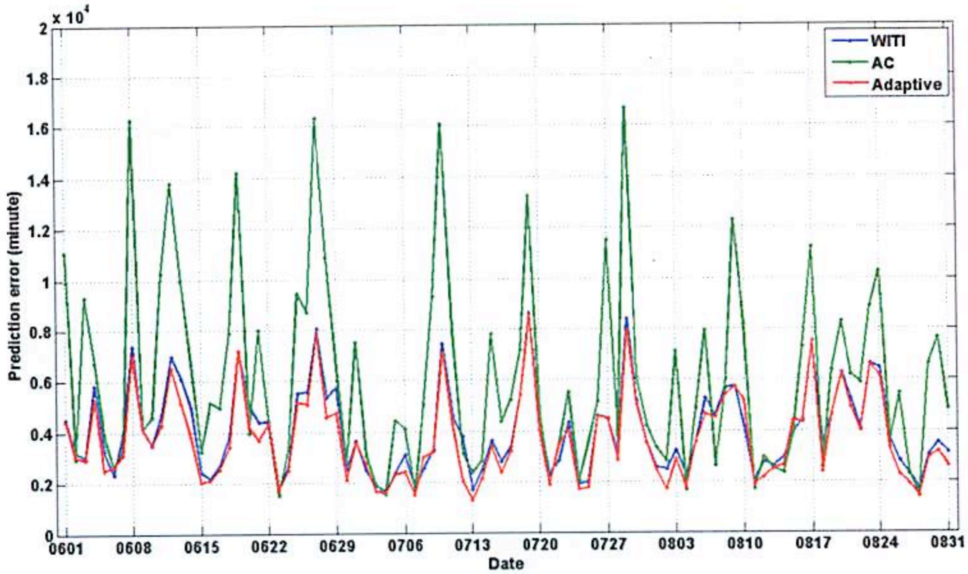



**Figure 7. One-hour delay prediction error for summer 2007.**

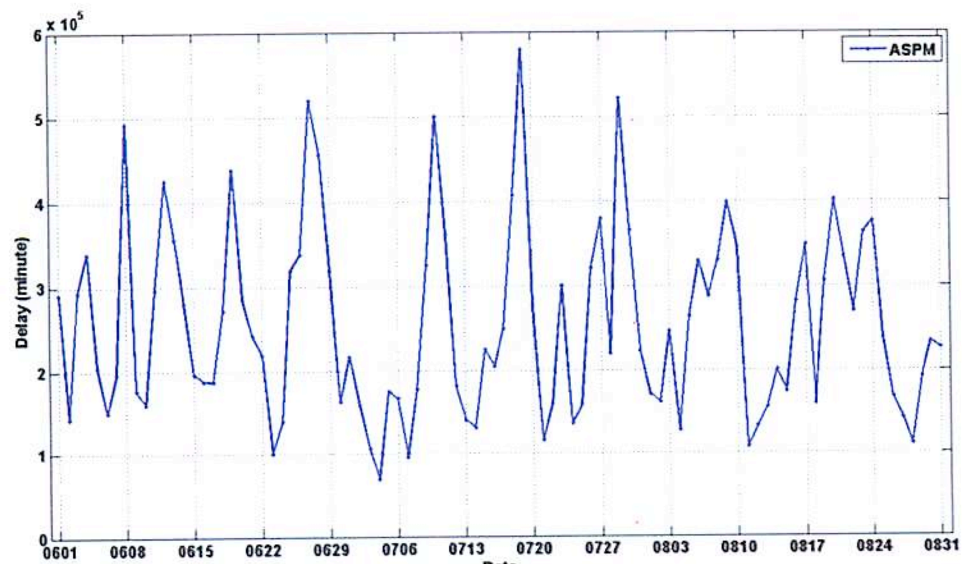



**Figure 8. ASPM delay during summer 2007.**

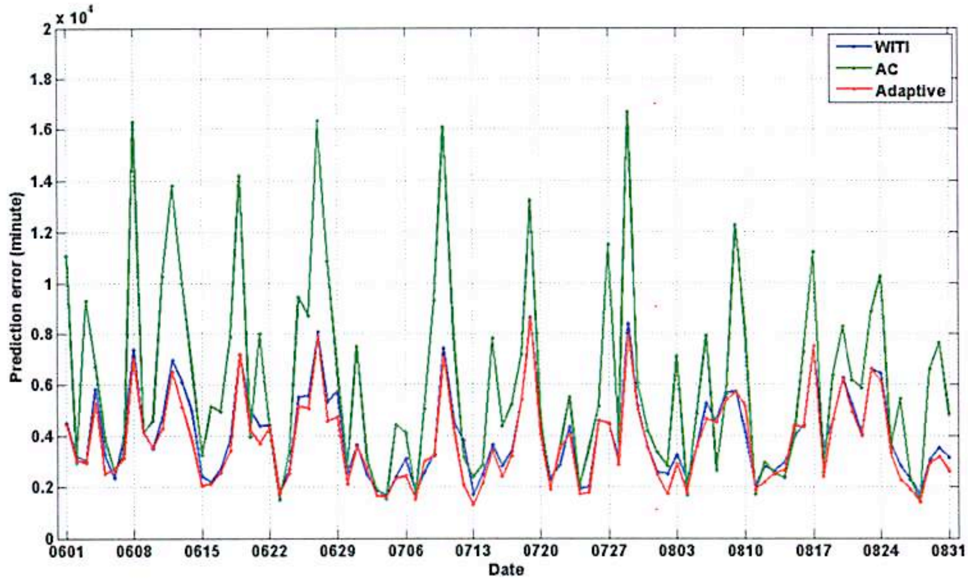



**Figure 9. Two-hour delay prediction error for summer 2007.**

## V. Conclusion

The paper presents a method to develop short-term delay prediction models for time intervals of up to two hours. Various linear autoregressive model structures were implemented to perform the delay prediction with WITI, predicted WITI, and reference traffic volume as exogenous inputs. The refined methodology for generating the WITI and predicted WITI, together with the high-update-rate CIWS weather product is well suited for short-term delay prediction. An adaptive method was implemented to provide both weather-related and non-weather-related delay predictions depending on the weather and air traffic condition. The models are compared using traffic and weather data for the summer months of 2007. The results show that WITI provides the most useful information for the one-hour prediction, while the best two-hour predictions rely on both WITI and predicted WITI. The reference air traffic volume provides non-weather-related information, which is useful on non-convective weather days. This paper is the first to study short-term real-time air traffic delay prediction using WITI and predicted WITI. The study should help traffic flow management in guiding flow control decisions and in identifying the strategies to reduce delays, cancellations, and costs during the day of operations in various weather conditions.

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